Small-Scale (Flash) Flood Early Warning in the Light of Operational Requirements: Opportunities and Limits with Regard to User Demands, Driving Data, and Hydrologic Modeling Techniques

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Abstract

In recent years, the Free State of Saxony (Eastern Germany) was repeatedly hit by both extensive riverine flooding, as well as flash flood events, emerging foremost from convective heavy rainfall. Especially after a couple of small-scale, yet disastrous events in 2010, preconditions, drivers, and methods for deriving flash flood related early warning products are investigated. This is to clarify the feasibility and the limits of envisaged early warning procedures for small scale catchments, hit by flashy heavy rain events. Early warning about potentially flash flood prone situations (i.e., with a suitable lead time with regard to required reaction-time needs of the stakeholders involved in flood risk management) needs to take into account not only hydrological, but also meteorological, as well as communication issues. Therefore, we propose a threefold methodology to identify potential benefits and limitations in a real-world warning/reaction context.

First, the user demands (with respect to desired/required preparation times, warning products, etc.) are investigated. Second, focusing on small catchments of some hundred square kilometers, two quantitative precipitation forecasts (including probabilistic QPFs) are spatially and temporally verified. Third, considering the user needs, as well as the input parameter uncertainty (i.e., foremost emerging from an uncertain QPF), a feasible, yet robust hydrological modeling approach is proposed on the basis of pilot studies with deterministic, data-driven, and simple scoring methods. Our contribution delivers a synopsis of the already acquired results for real-world (sub-)mesoscale catchments, comprising investigations of the aforementioned three methodological pillars. An appropriate approach for deriving hydrological forecasts/prognoses relevant for flash flood early warning is concluded from the presented results.

1 Introduction

For Saxony, considering the last two decades, the hydrologically most intense and most disastrous events occurred in August 2002, August/September 2010, as well as June 2013 (LfULG, 2004, 2013, 2015). Total damage for the aforementioned events sums up to 9 billion Euros (ca. 6.1 in 2002, ca. 0.85 in 2010 and ca. 2.0 in 2013). Especially in August/September 2010, flashy events in small catchments caused large parts of total damages. In this light, the Saxon State Government mandated an independent commission to identify suggestions for improving flood risk management actions (Jeschke et al., 2010). One of the commission's demands was to line out the potentials and limits of small-scale flash flood early warning approaches (i.e., based on hydrological forecasts).

As the authority responsible for operational flood forecasting and warning, the Saxon Flood Center (SFC) drafted a corresponding project with a preferably holistic view on flood risk management procedures, especially, when it comes to small-scale and flashy events. Therefore, a threefold approach is proposed, aiming at (1) the assessment of the demands and requirements of potential users of early warning products; (2) the verification of driving meteorological data for the targeted spatio-temporal scales; (3) checking the usefulness of a preferably broad range of modeling approaches with regard to model skill, robustness, and regional applicability, for small, potentially ungauged basins. The paper at hand provides a short overview of the current state of work and illustrates a way towards an operational early warning system for small catchments in Saxony.

2 Methods

2.1 User Survey

To investigate the needs and demands of potential users of an envisaged flood early warning system for small, fast-responding catchments in Saxony, a quantitative survey was carried out, based on an online questionnaire. The questionnaire comprised 15 questions, with 12 multiple-choice questions, two questions with gradually-scaled answers, and one question for the submission of verbal comments. Strictly speaking, the survey comprised quantitative and qualitative elements. For the sake of brevity, the full questionnaire is not presented herein but can be found in Philipp et al. (2015).

The surveyed sample was selected systematically (i.e., not randomly) and included all legal users (i.e., according to the Saxon Flood Alarm Bylaw; HWMO, 2014) of SFC products ($n = 578$) who were reachable via email to be invited for participating in the online survey ($n = 491$). The interviewee affiliation spanned administration/authorities at local/district/state level, fire departments and civil protection agencies, as well as the private sector. It has to be stated that the interviewees did not represent lay people since they participate in the official flood management procedures on a legal and regular basis.

The survey results were evaluated using descriptive statistics and subgroup analyses by means of contingency tables. Therefore, given answers were investigated in an user-group specific manner, i.e., more than one variable is considered at a time (multivariate approach). A question to address was whether specific user groups answered differently or not. Such an effect can be induced by strongly differing sizes of sub-samples or indicate a truly diverse response behavior. The literature suggests χ^2-based dependency measures to clarify such questions (Sachs, 1999). For the present study, Cramér's V and χ^2-based p-values were used.

2.2 Verification of QPFs

The verification of meteorological data comprised two Quantitative Precipitation Forecasts (QPFs) which are operationally used by the SFC. The investigated QPFs are the deterministic Numerical Weather Prediction (NWP) COSMO-DE product (Baldauf et al., 2011) and the probabilistic "Quantile Forecast" (QF) for 16 specific areas in Saxony (cf. Figure 1), issued by DWD's Regional Service Center in Leipzig. The two QPFs are compared against a Quantitative Precipitation Estimate (QPE), emerging from rain gauge data, which was spatially interpolated (Ordinary Kriging) to derive areal precipitation estimates. Additionally, weather radar data (DWD's RADOLAN-RW product; Sacher et al., 2011) was employed as another QPE reference. A comprehensive overview of the herein considered QPFs and QPEs is given in Table 1.

DWD's Quantile Forecast represents a probabilistic, qualitative expert estimate of areal precipitation for the next 36 hours and consists of three values/quantiles per forecasting time step. Since the QF is issued for 16 specific areas in Saxony (i.e., river catchments with topographic partitioning according to elevation), verification was based on the comparison of areal rainfall for the mentioned 16 regions, and spanned a period from 04/2011 to 06/2014.

Table 1: Overview of the considered QPF and QPE products.

Product	Provider	QPF/ QPE	Type	Temporal resolution	Spatial resolution	Lead time	Update cycle
COSMO-DE	DWD	QPF	Deterministic NWP output (gridded)	1 h	2.8 x 2.8 km	21/27[*] h	3 h
Quantile Forecast (QF)	DWD-RWB LZ[+]	QPF	Probabilistic forecast of mean areal precipitation	6/12 h[−]	Forecast regions from ca. 600 to 2.700 km^2	36 h	12 h
Interpolated rain gauge data	DWD	QPE	89 stations for the area of Saxony plus 25 km buffer	1 h	1 x 1 km[~]	—	1 h
RADOLAN-RW	DWD	QPE	Rain gauge adjusted weather radar estimate (gridded)	1 h	1 x 1 km	—	1 h

[*]27 hours since 01.30.2014 15:00 UTC. [+]DWD's Regional Service Center in Leipzig. [−]Product comprises two consecutive 6-hour and two further 12-hour intervals. [~]Data gridded via Ordinary Kriging.

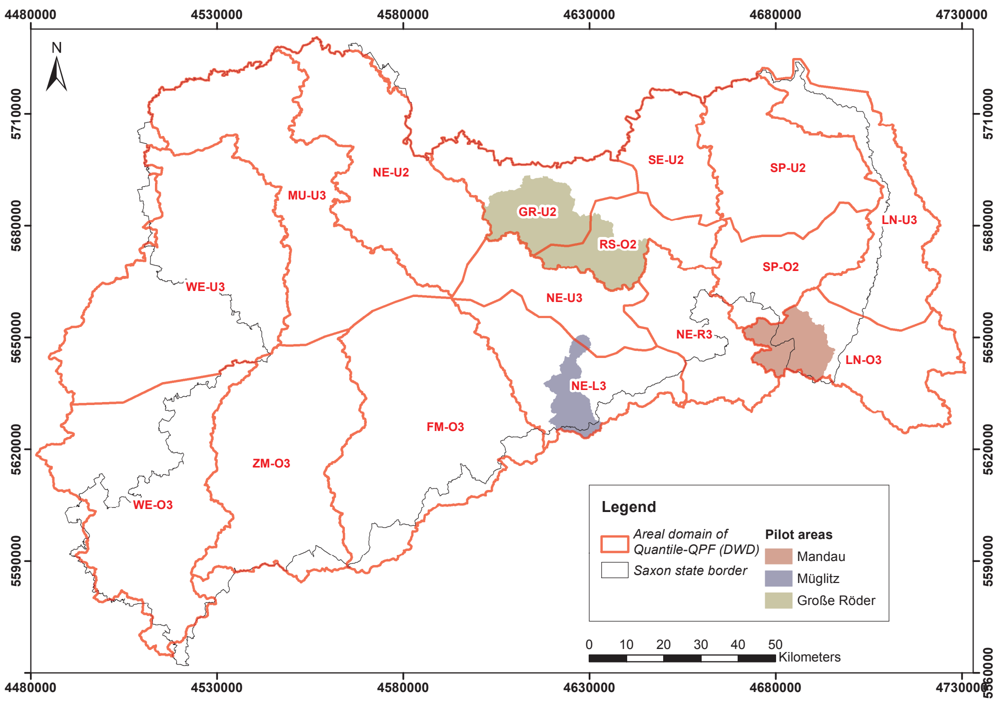

Figure 1: Overview map indicating the areal domain of the DWD Quantile-QPF for Saxony (16 regions; e.g., "FM-O3" indicates the parts of the Freiberger Mulde catchment above 300 m.a.s.l.). The area of the regions ranges between approximately 600 and 2.700 km^2. Furthermore, the hydrological pilot areas (cf. Section 2.3) are shown. Gauss conformal projection with reference at 12° E (Zone 4).

The comparison of areal rainfall was based on 6-hour sums, starting from 06:00 and 18:00 UTC. 6-hour sums were chosen to accommodate the most coarse temporal resolution of the investigated products, given by the Quantile-QPF. The QF features areal rainfall totals (for the 16 forecasting regions) for 0.9, 0.5, and 0.1 exceedance probability and two consecutive 6-hour and two further 12-hour intervals. The QF is updated twice a day (at 06:00 and 18:00 UTC) and therefore is a rather general QPF product. However, a main task of the herein presented verification was to evaluate the quality of this product against highly resolved NWP output (i.e., COSMO-DE).

A QPF/QPE comparison typically employs a number of tools and methods (Jolliffe and Stephenson, 2012), ranging from simple diagnostic (e.g., time series and totals comparisons, residual and bias analyses, scatter and frequency plots) to integral, quantitative methods. Analyses are often based on threshold-oriented contingency table evaluation and deliver typical verification/skill scores, e.g., FAR, POD (False Alarm Rate, Probability Of Detection) or combined products, e.g., ROC curves (Receiver Operating Characteristic; Fawcett, 2006). More detailed information on the herein employed QPF/QPE verification methodology (as well as concerning the results) can be obtained from Kerl and Philipp (2015).

2.3 Hydrological Modeling Approaches

Three different hydrological modeling techniques were implemented and applied for three pilot areas in Saxony (cf. Figure 1): first, a semi-distributed deterministic model (DeHM), second, a data-driven, neural-network model (DaHM) and, third, a simple classification model, based on the scoring of flood-relevant parameters (ScoHM). Subsequently, the modeling concepts and their application (with regard to calibration, data assimilation, etc.) are briefly described. Only snow-free conditions were regarded for model development and application.

Deterministic hydrological model (DeHM)

DeHM model's topology is based on a nodal representation of sub-catchments. Model calculations are performed for each node, whereas the calculation sequence is determined by the topological order of nodes; each model node holds all relevant parameters. Runoff generation is portrayed by the SCS Curve Number method. Runoff concentration is either modeled via an arbitrarily long cascade of linear reservoirs or via response-function convolution. Channel routing is described with either a time-lag function, a cascade of linear reservoirs, Muskingum method, or a translation-diffusion model. Since there are a number of multi-purpose and flood-retention reservoirs in the pilot areas, flood control was specifically included in the model.

Model calibration was based on event-specifically masked hydrograph data and employs a mixed performance criterion after Li et al. (2015). Data assimilation/state updating was realized with a simplified Kalman filter with error variances, following Blöschl et al. (2014). More details on the DeHM model and its application can be found in Schwarze et al. (2015).

Data-driven hydrological model (DaHM)

DaHM is an artificial neural network model, employing a feedforward two-layer perceptron (Hagan et al., 2002). The input vector features flow, rainfall, and cumulative rainfall data with the general 15-element form $I : [Q_{t-[0...3]}; P_{t-[0...3]}; P^c_{t-[0...6]}]$ (with hourly values of flow Q, rainfall P, and cumulative rainfall P^c). Adding to that, and depending on the considered lead time in the forecasting case, inputs that bear a rainfall forecast were included, e.g., for forecasting Q_{t+6}, the input P_{t+6} is added, for Q_{t+12}, $P_{t+6;\,t+12}$, respectively, whereas the P_{t+x} values portray specific QPF lead times.

The Levenberg-Marquardt algorithm was applied for network training, whilst allowing the number of hidden neurons range from 3 to 13. Event-wise masked hydrograph data and hourly areal rainfall were used for training.

Table 2: ScoHM scoring system.

	Description	Parameter bins	Sub-score range
Baseline susceptibility	Mean catchment slope	$<0.02/0.02/0.08/0.14/0.20$	0 to 4
	Catchment shape factor*	$<0.20/0.20/0.40/0.60/0.80$	0 to 4
	Degree of surface sealing	$<0.05/0.05/0.20/0.35/0.50$	0 to 4
	Proportion of fast runoff components[+]	$<0.10/0.10/0.23/0.37/0.50$	0 to 4
Dynamic susceptibility[~]	SPI over the last 30 days[−]	$-3/-2/-1/0/1/2/3$	-3 to 3
	Precipitation sum over the last 7 days	Sub-score percentiles[&] based on actual data from 01/2010 to 09/2015	0 to 4
	Precipitation sum over 12/24/48 hrs[#]		0 to 4
	Linear reservoir outflow[§]		0 to 4
Total susceptibility score			-3 to 31

*Catchment being more circular for values near unity. [+]According to Peschke et al. (1999). [−]SPI values rounded to integers. [~]In contrast to Collier and Fox (2003), snow-specific dynamic sub-scores were not considered. [#]Only highest sub-score is considered. [§]Linear reservoir being charged with hourly precipitation. [&]Percentiles: $<$ 75th/75th/90th/95th/99th.

15 training runs were evaluated for each specific hidden-neuron configuration and the best network was selected. Schwarze et al. (2015) give more details on the training and validation of the DaHM model.

Scoring model (ScoHM)

The employed scoring model resembles the Flooding Susceptibility Assessment approach proposed by Collier and Fox (2003). The method is twofold; first, a baseline susceptibility is derived, based on morphological features, e.g., slope, land cover, etc. Second, a time-variant, dynamic susceptibility is calculated, incorporating the Standardized Precipitation Index (SPI; Edwards and McKee, 1997), cumulative precipitation measures, and the response of a linear reservoir being charged with hourly precipitation.

The scoring is carried out according to Table 2; baseline sub-scores and the SPI sub-score are mapped linearly, according to the range of each respective morphological feature. For the remaining dynamic susceptibility sub-scores, frequency analyses were applied to deliver specific percentiles that are in turn connected to specific sub-score values, e.g., P-sums within the 75th–90th percentile-range of the data result in a sub-score of 1, etc. The method requires only one effective parameter, namely the recession constant of the incorporated linear reservoir, which was manually calibrated to a global value of 8 h.

In contrast to the DeHM and DaHM models, the ScoHM approach does not rely on observed flow data, neither in the sense of directly including auto-correlative signals, as applies for the data-driven DaHM model (in form of the Q_{t-x} inputs), nor indirectly via data assimilation/state updating, as applies for the deterministic DeHM model. Therefore, the ScoHM approach might offer a robustly transferable methodology towards prediction in small, ungauged basins.

3 Results

3.1 User Survey

Herein, the most important results of the user survey (cf. Section 2.1) are presented in a concise manner; a more detailed presentation can be found in Philipp et al. (2015). The response rate was 76 % (n = 373), which is extraordinarily high (with 69 % or n = 339 completely answered questionnaires) and is mainly a result of the systematic sampling (cf. Section 2.1). For 11 out of 15 questions, user-group specific replies were not distinguishable in a statistical sense. The outcomes of the statistical analysis of the survey data can be summarized as follows:

Information and pathways: (1) The interviewees request selective, event-related information or inform themselves on an event-related basis (rather than on a regular basis). (2) 37 % of all users trust that a more regular and more frequent distribution of warning products will provide increased security for their management decisions, even if the meteorological and hydrological trend remains unchanged. (3) All groups, except the group "private persons", attach greatest importance to the internet in contrast to other communication channels (e.g., fax, video text, voice mail). The official flood warnings issued by fax or email are also used for information by a majority of users. (4) A high availability of warning services and products is deemed important by a vast majority of users, especially in the case of flooding.

Flood warning products: (1) A short-termed, but more precise warning is preferred over a long-term estimation, carrying presumably more uncertainty. (2) The majority of users ($> 65\,\%$) are interested in receiving a possibly reliable forecast of the peak water level. 45 % of users would appreciate being informed about the peak timing. (3) Most popular products for fulfilling early warning purposes are forecasted hydrographs with uncertainty bands (about 50 % of all persons interviewed), as well as a catchment-oriented classification products ("traffic light", approximately 40 % of all persons interviewed).

Lead time: (1) The minimum required lead times amount to ≤ 3 h (9 % of users), ≤ 6 h (27 %), ≤ 12 h (50 %), ≤ 24 h (83 %), ≤ 72 h (98 %). (2) A lead time of ≤ 12 h is deemed to be adequate by a slim majority of users in small catchments ($< 200\,\mathrm{km}^2$).

Miscellaneous: (1) The interviewed user groups vary significantly in terms of the replies given when being asked for the requested updating frequency of flood warnings and their communication via email or fax. (2) Furthermore, the interviewees of various user groups specifically replied to the questions concerning the quality of current SFC products and the quality of the work of the SFC. (3) Moreover, no significant differences in the response behavior of the various user groups could be identified by statistical means.

3.2 Verification of QPFs

The investigated QPFs (COSMO-DE and QF) were compared against areal precipitation estimates, based on gridded rain gauge data, and, additionally, a radar-based QPE (RADOLAN-RW product). First, threshold exceedance frequencies were derived from the QPEs and QPFs (cf. Figure 2). COSMO-DE delivers exceedance frequencies which are close to the ones derived from rain gauge data. RADOLAN (QPE) underestimates the threshold exceedance frequencies from rain gauge data, whereas the chance of underestimation is higher at lower thresholds, and vice versa. The dashed line at an exceedance frequency of 10 indicates that thresholds greater than 10 mm/6 h should be evaluated with caution, due to limited data sample sizes (i.e., less than 10 events in the investigated period). Due to QF-product related conventions (areal precipitation sum < 4.5 mm/6 h is set to zero), the exceedance frequencies of the QF remain constant for thresholds < 4.5 mm. Threshold exceedances drawn from the QF's 50th and 10th percentile are generally more frequent than the observed ones (i.e., from rain gauge data), whereas the 90th percentile underestimates observed frequencies.

Second, for a more in-depth view at the regarded QPFs, the contingency-based measures POD and FAR were evaluated (Figures 3 and 4). Again, due to the product-specific convention of the QF, the results for the thresholds < 4.5 mm/6 h are identical. Following Winterrath et al. (2012), a minimum of 10 observed or predicted threshold exceedances should be required for the calculation of skill scores. Therefore, POD and FAR were not always evaluated for higher thresholds. Generally, higher precipitation thresholds are connected with lower POD and lower FAR values, and vice versa. Furthermore, the skill variance amongst the forecast areas increases with increasing precipitation thresholds. POD = FAR indicates a boundary threshold for which the considered QPF has no predictive benefit anymore. This boundary is not reached for both QPFs, concerning the investigated thresholds. Finally, for the regarded QPFs, COSMO-DE exhibits the best performance with regard to POD/FAR relations and skill variance.

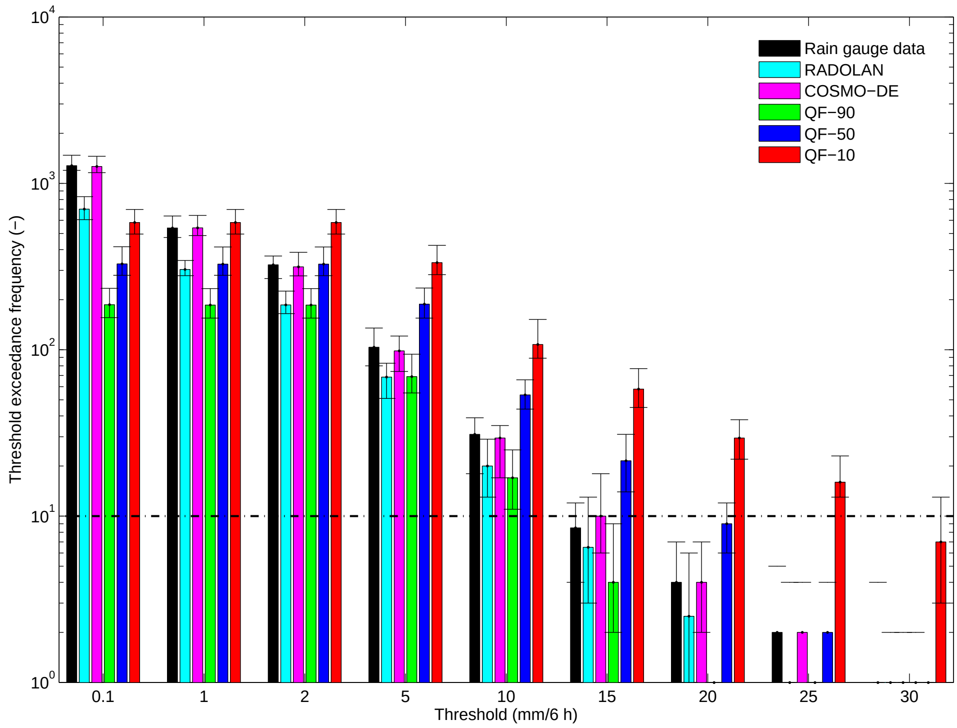

Figure 2: Threshold exceedance frequencies of 6-hourly areal precipitation sums for QPEs (gridded rain gauge data, RADOLAN-RW) and QPFs (COSMO-DE, Quantile Forecast) from 04/2011 to 06/2014. The bars show the median of exceedance frequencies for the respective precipitation products for the 16 forecast areas (cf. Figure 1). The whiskers illustrate the minimum and maximum values; the dashed line depicts an exceedance frequency of 10.

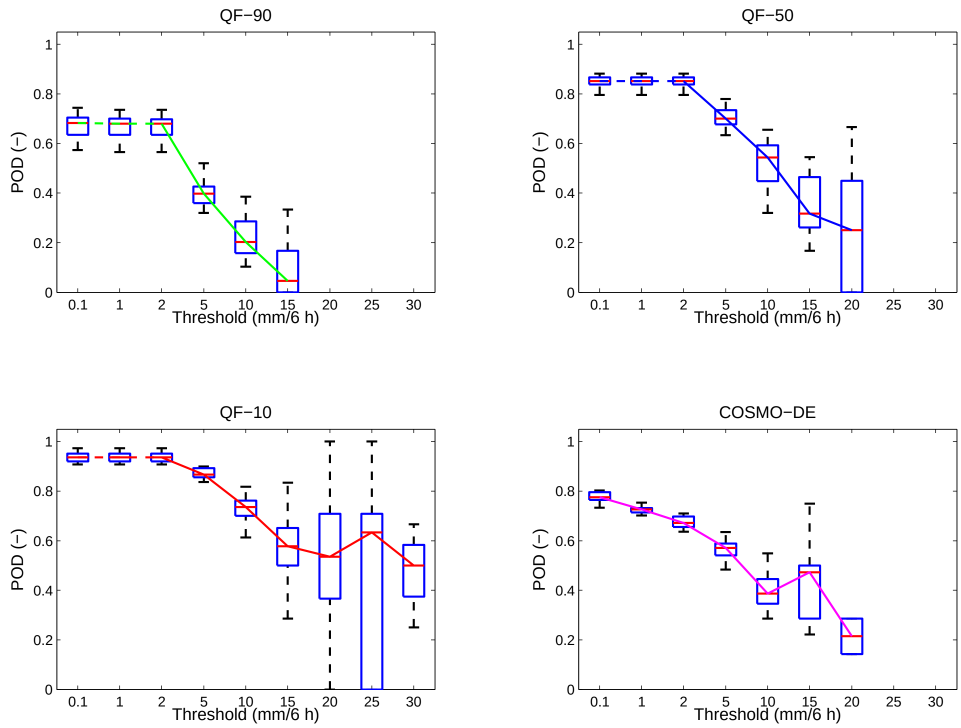

Figure 3: Probability Of Detection (POD) according to thresholds of areal precipitation sums ranging from 0.1 to 30 mm/6 h for the Quantile Forecast and COSMO-DE from 04/2011 to 06/2014. The box plots indicate the spread of POD over the 16 forecast areas.

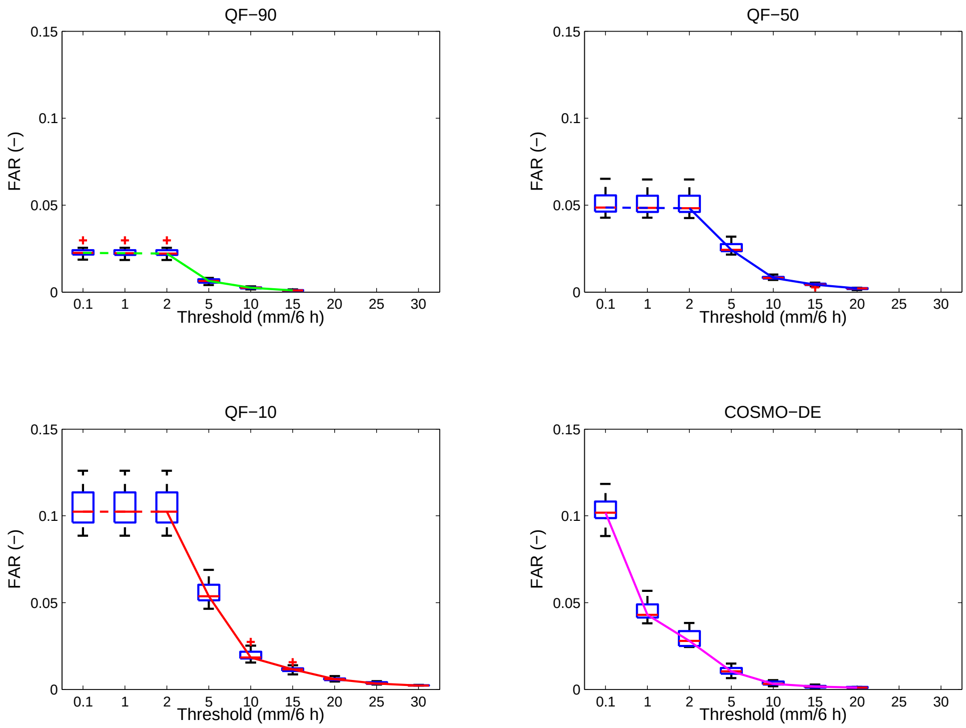

Figure 4: False Alarm Rate (FAR) according to thresholds of areal precipitation sums ranging from 0.1 to 30 mm/6 h for the Quantile Forecast and COSMO-DE from 04/2011 to 06/2014. The box plots indicate the spread of FAR over the 16 forecast areas.

3.3 Hydrological Model Validation

The three presented models (DeHM, DaHM, ScoHM) were applied for the three aforementioned pilot areas (cf. Figure 1). The herein investigated QPEs (gridded rain gauge data and RADOLAN data) and QPFs (COSMO-DE and QF; cf. Sections 2.2 and 3.2) were used as meteorological drivers (for the current state of work, ScoHM was charged with rain gauge data only). Validation for the DeHM and DaHM models is straightforward since modeled hydrographs are simply compared against observed ones. Model evaluation is a bit more delicate for the ScoHM results, since the ScoHM output (i.e., dimensionless scores) does only qualitatively correlate with observed flow values. Therefore, a quantile-mapping procedure (Piani et al., 2009) was applied to relate thresholds of Q with corresponding total-score values.

Model performance was (besides other integral measures as RMSE, NSE, etc.) evaluated on the basis of threshold-oriented contingency table analyses, i.e., it is checked if modeled output matches/exceeds a certain observed flow/alarm level or not. More specifically, the variation of threshold values delivers a set of corresponding skill scores, e.g., POD values with corresponding FARs. These POD/FAR tupels were used to establish catchment-specific ROC curves (Fawcett, 2006). The ROC curves were finally integrated to deliver AUC (Area Under Curve) values, with AUC near unity for a near-perfect model prediction and near 0.5 for no predictive skill. For brevity, results are presented and discussed for the Mandau catchment only, featuring four river gauges.

Generally, different combinations of lead times and update cycles (i.e., the time after which a new forecast is calculated) were investigated; herein, results for an update cycle length of 12 h are presented. Event-specifically masked, hourly hydrograph data and hourly rainfall observations were used during model validation. Data which were used in model calibration/training were not used for validation purposes. Data originated from the period of 2010 to 2015. Figure 5 comprehensively shows the validation results at four gauges within the Mandau pilot region. For the QF-QPF, results for the 50th percentile are exemplarily shown.

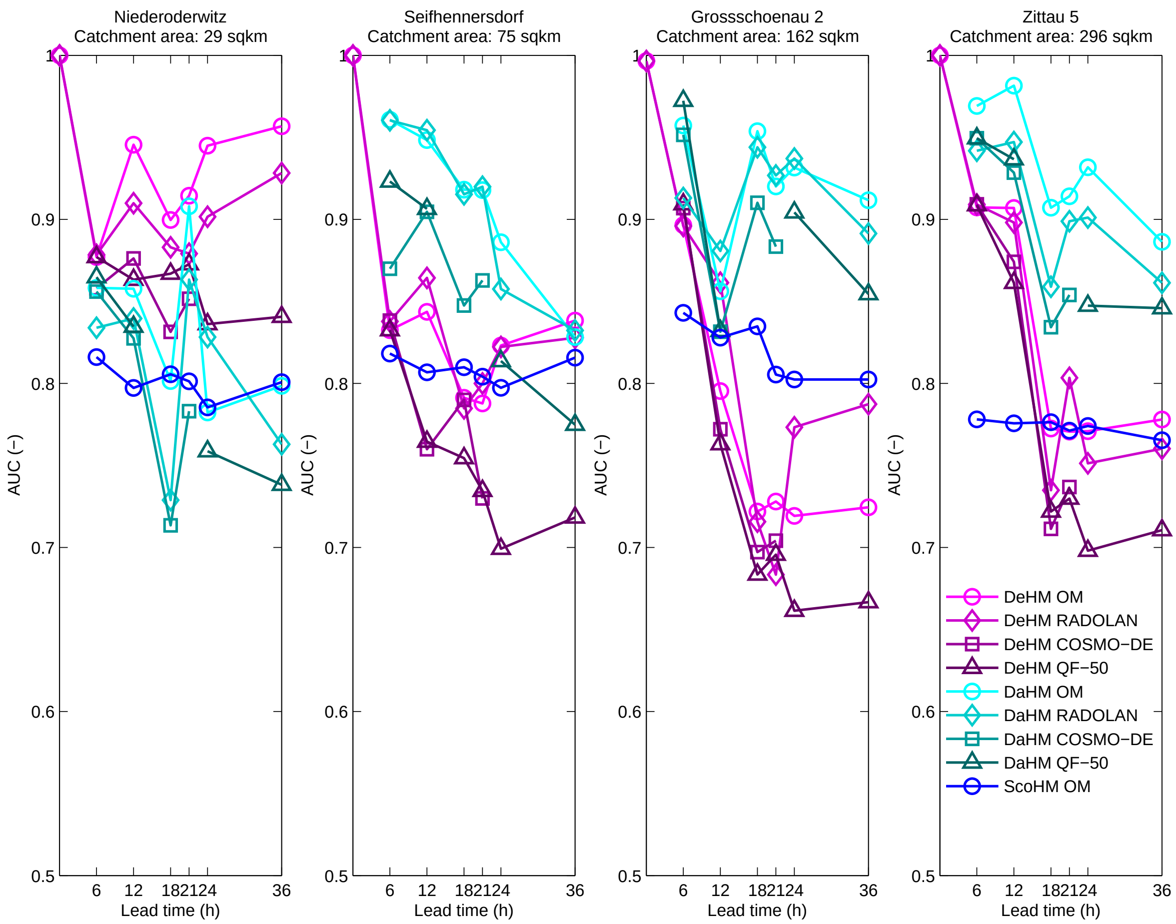

Figure 5: Results of hourly, threshold-oriented model evaluation for DeHM, DaHM and ScoHM output in the Mandau pilot region. Lead times range from 6 to 36 hours, update cycle is 12 hours. OM: ombrometer data (i.e., gridded rain gauge data); RADOLAN: QPE from weather radar scans; QF-50: 50th percentile of Quantile Forecast; COSMO-DE: NWP output. Skill for DeHM at a lead time of zero is based on true model output after assimilation/updating and can be slightly smaller than unity (e.g., apparent for Großschönau 2).

For the smallest sub-catchment, Niederoderwitz (29 km^2), DeHM performs best; for the three larger sub-catchments, DaHM features the highest AUC values. However, DeHM and DaHM performance trends to decrease with increasing lead time; ScoHM features a quite constant/robust AUC development. The reason might be that for shorter lead times (6 h) the auto-correlative Q_{t-x} signal, included directly or indirectly in the DeHM and DaHM model, leads to improved performance. This does not apply for the ScoHM results, since the model does not rely on observed flow data. Generally, ScoHM exhibits AUC values around 0.8 which indicates a good overall predictive skill, foremost, when keeping in mind the generality and straightforwardness of the model approach.

It can be seen from Figure 5 that QPE data delivers highest predictive skill; incorporating RADOLAN and rain gauge data as precipitation inputs leads to similar skill. Predictive skill under QPF data (QF and COSMO-DE) is generally lower. For different QPFs as drivers, resulting skills do not differ greatly. Apparently, the observed differences in QPF quality (cf. Section 3.2) do not systematically impact hydrological model skill. Finally, it is important to state that validation was carried out on the basis of hourly values; a more general evaluation, e.g., comparing only the highest values within a specific temporal window (e.g., 6 hours), would yield considerably higher skill scores.

4 Conclusions and Outlook

In this study, user demands, driving data, and hydrologic modeling techniques were evaluated within a real-word application context in order to illustrate a way towards a flash flood early warning strategy for (sub-)mesoscale catchments in Saxony. First, the results suggest that the majority of potential users of flood warnings would be satisfied with forecasting lead times of up to 24 hours and that users are foremost interested in predicted peak water/alarm levels (rather than peak timing). Second, on the basis of meteorological verification results, highly resolved NWP data seem to offer the best predictive skill, compared to more general, areally integrated products. Third, differences in the quality of meteorological driving data do not greatly influence hydrological model skill. Fourth, a clear statement on the superiority of one hydrological model over another cannot be made.

In fact, if simple classification models would be sufficient to satisfy warning needs (e.g., providing the information whether or not a specific threshold is likely to be exceeded in the next forecasting interval), results show that such a modeling approach (i.e., ScoHM) performs with favorable skill, compared to more sophisticated modeling techniques, and without introducing cumbersome parameter estimation problems and limited (DeHM) or even nonexistent (DaHM) regional transferability. However, overall forecasting skill always decreases with increasing randomness of driving events and conditions, i.e., the more rare/focused/intense the flood-causing processes and/or the longer the lead time, the smaller the chance of correct detection/warning.

Further research is currently carried out regarding the statewide implementation and comparative evaluation of the herein considered hydrological modeling approaches. Meteorological verification will be carried out for smaller spatio-temporal scales. ScoHM will be validated for QPF inputs. Generally, the set of QPFs will be extended to DWD's 21-member ensemble product, COSMO-DE-EPS. Thus, allowing a comprehensive probabilistic verification and validation. Another goal is evaluating model-specific extrapolation skill to propose a feasible regionalization methodology for deriving threshold-based warnings for ungauged basins.

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